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Production Forecasting in the Automotive Industry: Performance Analysis of Time Series Models Using the Box-Jenkins Method

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Abstract

In the realm of industrial engineering and management, production forecasting is a pivotal topic that profoundly influences productivity and the optimization of production processes. By developing a precise prediction model, companies can significantly enhance production planning, control production, minimize stoppages, optimize inventories, and boost machinery productivity. This study delves into the production processes of the SAIPA Automotive Group and proposes an accurate prediction model. Using statistical time series forecast models, including the Box-Jenkins method and the Rolling forecast approach, the study reveals that these models, particularly the Auto Regressive Integrated Moving Average eXogenous (ARIMAX) model, excel at daily production prediction. Conversely, the Auto Regressive Integrated Moving Average (ARIMA) and Autoregressive (AR) models demonstrate superior efficiency in trend-based production prediction. Additionally, the Seasonal Auto Regressive Integrated Moving Average (SARIMA) and Seasonal Auto Regressive Integrated Moving Average eXogenous (SARIMAX) models performed worse. The application of time series tools and the rolling forecast approach has also led to a notable reduction in model errors.

Keywords: Production forecasting, Time series models, Box-Jenkins, Rolling forecasting.

1 | Introduction

In today's highly competitive global markets, timely and cost-effective production is increasingly important. It requires the collaborative efforts of many stakeholders to develop effective strategies for supply chain management, production planning and scheduling, and the control and allocation of equipment and labor [1].

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Production planning is a managerial process that involves designing and planning an organization's production activities to optimize the use of available resources and ensure the efficient production of high-quality products and services [2].

In industrial engineering and management, production forecasting is a critical topic in production planning, significantly impacting productivity and the optimization of production processes. By developing an accurate forecasting model, companies can enhance production planning and control, reduce production time, minimize stoppages, optimize inventories, and increase machinery productivity [3], [4].

All forecasting tasks must address issues such as what to forecast, the forecasting method, the level of aggregation, the data used, and the forecast accuracy. Forecasting can be at various levels of aggregation, ranging from fully aggregated to semi-aggregated or fully disaggregated forecasts for short- and long-term periods. The data used in forecasting can be based on historical production, sales, arrivals, or reservations. Additionally, forecasts should be adjusted for specific events, such as holidays and special occasions [5].

In the SAIPA Automotive Group, six companies, Saipa, Pars Khodro, Saipa Citroën, Bonro, Zamyad, and Saipa Diesel, engage in the daily production of various car models. As with any manufacturing unit, the SAIPA Automotive Group has established a Master Production Schedule (MPS) from the outset of operations, taking into account available capacity for machinery and equipment, labor hours, raw materials, market demand, and other factors. This MPS is then used to formulate monthly and weekly plans, with the weekly production plan detailing daily production targets.

However, in practice, production often deviates from the planned schedule, underscoring the necessity for accurate production forecasting to aid decision-makers and managers. This research aims to examine production in the SAIPA Automotive Group and to present an accurate production forecasting model. To this end, statistical time-series forecasting models, including the Box-Jenkins method and the Rolling forecasting approach, have been used to forecast production for the six car manufacturing companies within the SAIPA Automotive Group.

This paper is organized as follows: Section 2 reviews the related literature. Section 3 describes the research methodology, including the methods used for data collection and preprocessing, implementation of forecasting models, model evaluation, and the results obtained. Section 4 presents the discussion and conclusions of the research.

2 | Literature Review

Time series forecasting models use historical data to predict future values. These models include univariate linear or nonlinear time series models and multivariate linear and nonlinear time series models. *Table 1* briefly reviews the literature that has employed time-series forecasting models. Based on the studied articles, among the Box-Jenkins models, the Auto Regressive Integrated Moving Average (ARIMA) model has been most frequently used for forecasting, which is certainly related to the dataset's characteristics. Additionally, in recent years, hybrid models that combine several time series models have become more prevalent.

Table 1. Examples of research on solving forecasting problems using time series models.

	Reference	Description And Application	Solution Method	Data Characteristics
1	Singh and Mishra [6]	Retail price forecasting	Box–Jenkins	Univariate (with exogenous variable)
2	Ghomi and Forghani [7]	Forecasting the expected number of passengers using two techniques, Box-Jenkins and artificial neural networks. The superior performance of Box-Jenkins models is demonstrated.	Box–Jenkins and ANN	Univariate (with exogenous variable)
3	Ni et al. [8]	Forecasting metro passenger flow. A parametric and convex optimization approach, called Optimization and Prediction with Combined Loss Function (OPL), is proposed to combine SARIMA models jointly.	SARIMA + OPL	Univariate (with exogenous variable)
4	Milenkovic et al. [9]	Forecasting passenger flow	ARIMA and SARIMA	Univariate
5	Chen et al. [10]	Forecasting public transportation (bus) travel demand	ARMA and ARIMA	Univariate
6	Su and Ye [11]	Forecasting public transportation (bus) travel demand	ARMA and ARIMAX	Univariate (with exogenous variable)
7	Ghauri et al. [12]	Evaluating two econometric models for forecasting imports and exports for the Fiscal Year (FY) 2020	Box–Jenkins	Univariate(with exogenous variable)
8	Guleryuz [13]	Forecasting disease spread. Among box-Jenkins models, ARIMA, ETS, and RNN-LSTM are employed. ARIMA, with the lowest AIC values, is selected as the best model for the total number of cases, total case growth rate, number of new cases, total deaths, total death growth rate, and number of new deaths.	Box–Jenkins, ETS, and RNN-LSTM	Univariate (with exogenous variable)
9	Hadwan et al. [14]	Forecasting the expected number of cancer patients	ARIMA and BPNN	Multivariate (with exogenous variable)
10	Yasmin and Moniruzzaman [15]	Forecasting agricultural area, production, and yield in Bangladesh	Box–Jenkins	Univariate (with exogenous variable)

The time series models used in this research are briefly introduced below.

2.1 | Autoregressive

The Autoregressive (AR) model is a linear model that describes the relationship between a time series's previous values and its current value. In this model, the current value of the time series is modeled as a linear combination of its previous (p) values and a random variable with mean zero (usually noise or error). The formula for the AR(p) model is as follows:

$$X_t = \sum_{i=1}^{p} \varphi_i X_{t-i} + \varepsilon_t + C \quad (1)$$

Here: X_t represents the current value of the time series. c is a constant. φ_i are the model parameters that indicate the dependency of previous values on the current value. ε_t is a random variable with a mean of zero, representing noise.

2.2 | Moving Average

The Moving Average (MA) is one of the primary models in time series analysis used for modeling and forecasting time series data. This model averages the values of sequential noise or errors in the time series. In an MA (q) model, the current value of the time series is modeled as a linear combination of the previous (q) values of noise or errors and a random variable with a mean of zero. The formula for the MA (q) model is as follows:

$$X_t = \mu + \varepsilon_t + \theta_1\varepsilon_{t-1} + \cdots + \theta_q\varepsilon_{t-q} = \mu + \sum_{i=1}^{q} \theta_i\varepsilon_{t-i} + \varepsilon_t \tag{2}$$

Here: X_t represents the current value of the time series. μ is the mean of the time series. ε_t is a random variable with a mean of zero, representing the noise or error of the model. θ_i are parameters indicate the dependency of previous noise or error values on the current value.

2.3 | Auto Regressive Integrated Moving Average

The Auto Regressive Integrated Moving Average (ARIMA) model is a linear model composed of two main components: the AR and MA models. In this model, the relationship between the previous values of the time series and the MA of the sequential noise or errors is modeled. The ARIMA model is an extension of the ARMA model, incorporating three main elements: AR, MA, and I (integration). This model is used for modeling and forecasting non-stationary time series and provides more accurate predictions by fitting parameters to real data. The formula for this model is equivalent to the following expression:

$$X_t = \varepsilon_t + \sum_{i=1}^{p} \varphi_i X_{t-i} + \sum_{i=1}^{q} \theta_i\varepsilon_{t-i} \tag{3}$$

2.4 | Seasonal Auto Regressive Integrated Moving Average

The Seasonal Auto Regressive Integrated Moving Average (SARIMA) model is an extension of the ARIMA model used for modeling time series with seasonal patterns. This model uses AR, MA, I (integration), and seasonal AR and MA components to model and forecast time series with seasonal patterns.

2.5 | Auto Regressive Integrated Moving Average eXogenous

The Auto Regressive Integrated Moving Average eXogenous (ARIMAX) model is an extension of the ARIMA model that incorporates external or exogenous variables for time series modeling. This model allows for the modeling of the effect of external variables on the time series.

2.6 | Seasonal Auto Regressive Integrated Moving Average eXogenous

The Seasonal Auto Regressive Integrated Moving Average eXogenous (SARIMAX) model is an extension of the SARIMA model that incorporates exogenous variables to model seasonal patterns in time series. This model uses AR, MA, and I components, seasonal AR and MA components, and external variables to model time series with seasonal patterns and external-variable influences.

2.7 | Model Performance Evaluation Criteria

To evaluate model performance and select the best model, evaluation criteria from the time series literature, including Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Log-Likelihood (LLF), have been used. AIC and BIC are criteria for evaluating the quality of a statistical model. These criteria compare the model's simplicity with the accuracy of its predictions. Lower AIC and BIC values indicate a better, simpler model. LLF is the logarithm of the likelihood function, which indicates how well the model fits the data. Higher LLF values indicate a better fit of the model to the data. In addition to the AIC, BIC, and LLF performance evaluation criteria used in statistical models, this study uses Mean Absolute Error (MAE) which is the average absolute error between predicted and actual values; Mean Squared Error (MSE) which is the average squared error between predicted and actual values; Root Mean Squared Error (RMSE) which is the square root of the average squared error between predicted and actual values; and R-squared which shows the ratio of the MSE to the mean squared actual values, to evaluate the prediction models.

3 | Research Methodology

The Box-Jenkins method is a well-known approach to time series analysis and forecasting, used to model and predict time series data. In this study, the Box-Jenkins method is employed to implement time series models. This method first fits an ARIMA model to the time series under investigation and then provides better predictions by estimating the model parameters from the actual data. The research method is shown in Fig. 1. The main steps of the Box-Jenkins method are as follows:

Data understanding

In this step, the time series under investigation is analyzed to identify various structures such as stationarity, trend changes, seasonal patterns, and random values. In this study, after data cleaning, additive models and exponential smoothing are used to plot decomposed time series charts to identify trends and seasonal patterns. Additionally, to examine the stationarity of the time series and determine the appropriate time lag, the Dickey-Fuller statistical test, autocorrelation, and correlation coefficient plots are used.

Model implementation and parameter estimation

After understanding the dataset, ARIMA model parameters p, d, and q are calculated using methods such as autocorrelation functions, statistical tests, or the auto-ARIMA model. In this study, the initial parameters of the time series models are determined by implementing and running the auto-ARIMA model. Auto-ARIMA is a model that uses grey search and local optimization methods to find the best combination of hyperparameters for univariate time series models. This method searches for the best time series model that fits the data within the specified range of hyperparameter values, and reports the best model. Given the use of local optimization and top-down search concepts, the auto-ARIMA model may also identify simpler models with fewer coefficients than the reported model for the time series data. Therefore, the upper bound of the ARIMA model coefficients is determined using this model, and then models with smaller coefficients are implemented and executed.

Model validation and evaluation

Time series forecasting models are created using the estimated parameters. In this study, all time series models, including AR, MA, ARMA, ARIMA, SARIMA, ARIMAX, and SARIMAX, are implemented and evaluated over the hyperparameter range. To validate and evaluate the model, residual correlation tests and normality checks of the error distribution are performed using correlation and Q-Q plots of the model errors.

Selecting the best model

At this stage, after fine-tuning the hyperparameters, the best models are identified based on evaluation criteria, including AIC, BIC, LLF, MSE, RMSE, and MAE.

Forecasting and conclusion

Using the final time-series model, future time-series predictions are provided, and the model's validity is assessed. In this study, to examine the best model's results and improve its accuracy, a rolling (moving) forecast approach is used.

3.1 | Data Understanding

The data used in this study includes the daily production statistics of companies in the SAIPA automotive group, encompassing daily production characteristics, annual production plans, and weekly production plans for Saipa, Pars Khodro, Saipa Citroën, Bonro, Zamyad, and Saipa Diesel from the beginning of 2023 to the end of December 2024. *Fig. 2* shows the production trend over time for the companies in the SAIPA automotive group.

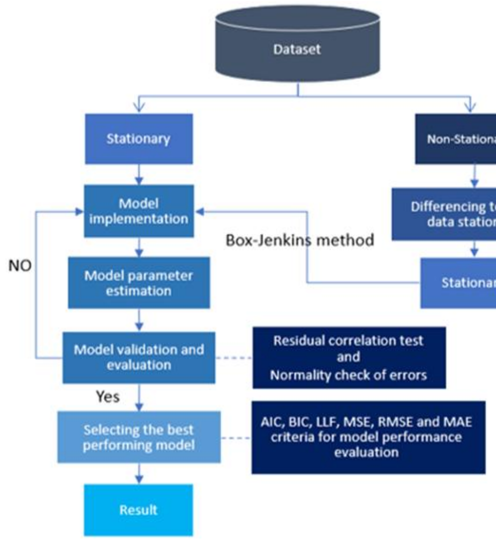

Fig. 1. Research method structure.

By examining the covariance and correlation values shown in *Fig. 3*, contrary to expectations, there is no strong positive correlation between the production plan and the production of SAIPA group companies, especially at Zamyad and Saipa Diesel. It indicates that these companies have fallen short of their production targets. Additionally, negative correlations between the production or production plans of one company and another suggest a high likelihood of unfairness in the supply chain in some cases.

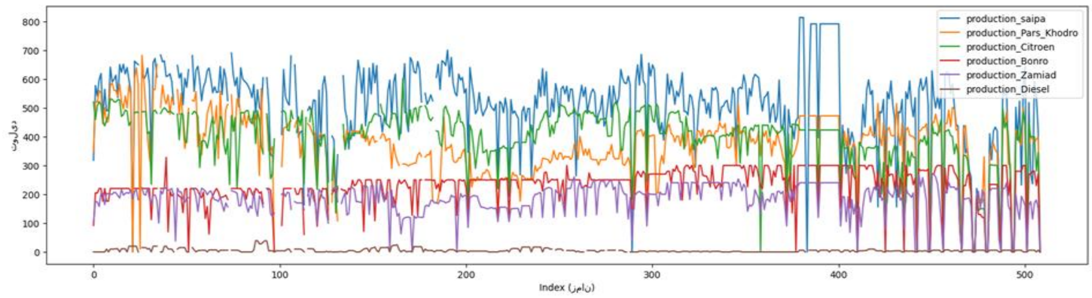

Fig. 2. Production trend over time for SAIPA automotive group companies.

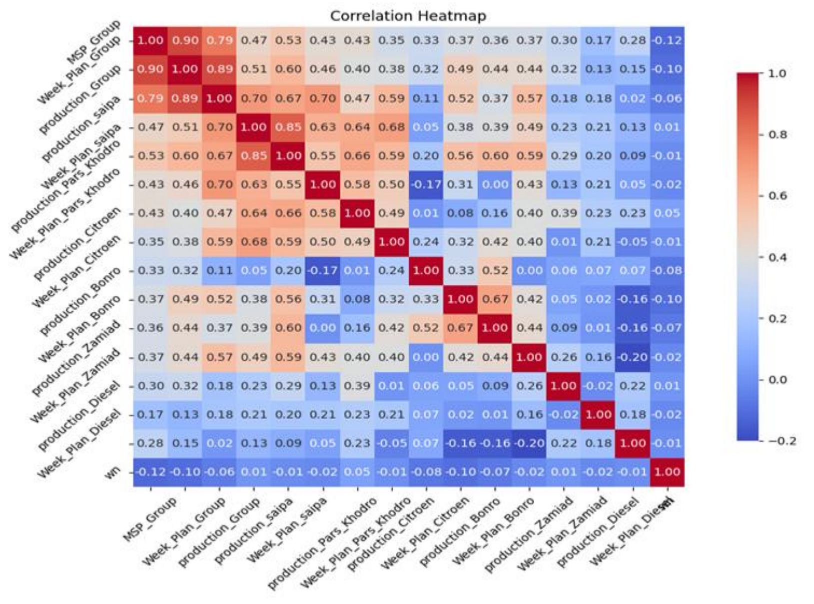

Fig. 3. Covariance values between production plan and production for SAIPA group companies.

3.1.1 | Data cleaning

Data cleaning is the process of identifying and handling errors, duplicates, and irrelevant data from a raw dataset to prepare it for analysis. Generally, data cleaning involves three steps: 1) removing duplicate data, 2) identifying and handling missing data, and 3) identifying and handling outliers. The operations performed to clean the dataset used in this study are briefly explained below.

I. Identifying duplicate data: the dataset contains no duplicates.

II. Identifying and handling missing data: the missing data identified in the dataset pertains to holidays during the specified time period when the factories were not in production. Given the time series nature of the dataset, two scenarios are considered: 1) Missing values are replaced with zero due to factory closures. This scenario preserves the information and knowledge within the data by recording the actual event in the dataset. Still, it may complicate data patterns, potentially affecting the accuracy of predictive models, and 2) Missing values are replaced with the production value of the nearest date after the holiday, based on the assumption that no production occurs on holidays. This argument reduces data complexity and may increase the accuracy of predictive models.

In this study, a combination of these two scenarios is used to handle missing values. During official national holidays, missing values are set to 0. However, on days when one or more factories were closed for any reason, these values are replaced with the next period's value in the time series.

III. Identifying and handling outliers: given that data collection was conducted with great care and reviewed multiple times, no erroneous records are present in this dataset, and all records accurately reflect real events. Therefore, outliers identified by statistical tests contain useful information about production trends in the companies, and no action has been taken regarding these data in this study.

3.1.2 | Identifying seasonal patterns in time series

In the literature, the behavioral patterns or change models of a time series are divided into four components: trend, cycle, season, and irregular variations or residuals. By plotting the time series against time, these components can be distinguished, leading to a better understanding of the time series data. Identifying seasonal patterns in time series data can be done using several different methods. In this study, additive models, which consider the time series as the sum of three components: trend, seasonal patterns, and random values, and the Local Regression (LOESS) method, which decomposes the time series into seasonal and trend components using local smoothing, are used to discover and identify seasonal patterns. *Fig. 4* shows the trends and patterns discovered in the daily production dataset of the Saipa company using additive models and exponential smoothing.

According to the charts plotted by these models, the dataset does not exhibit a clear upward or downward trend and shows a nearly sinusoidal behavior over time. Therefore, regarding seasonality, as indicated, the data has been identified to have seasonal patterns. This pattern is particularly associated with additive charts for weekend holidays. Irregular variations are changes caused by random and unpredictable factors. In research, these values are typically removed from the time series and treated as outliers. Still, in this study's dataset, for the reasons previously mentioned, no action has been taken regarding these values.

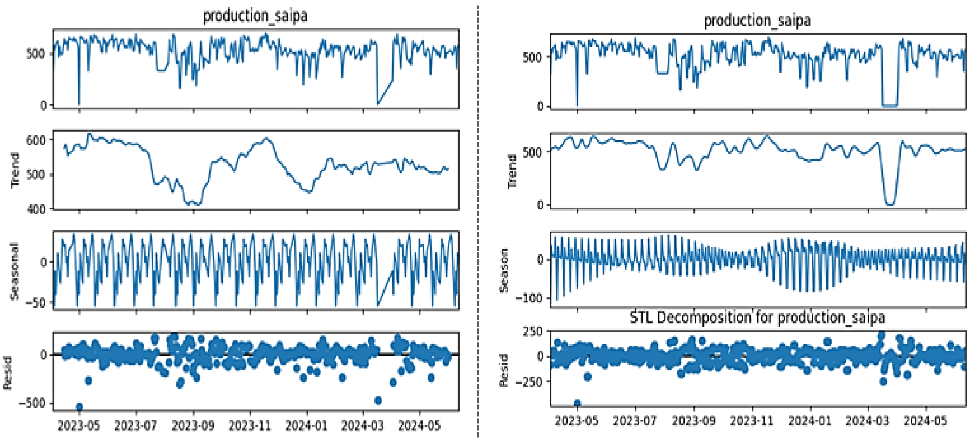

Fig. 4. Display of production trend, seasonal patterns, and residuals using the exponential smoothing model (right) and additive model (left) for the Saipa company.

3.1.3 | Stationarity

Stationarity of a time series is a necessary condition for achieving reliable forecasts. There are several statistical tests for examining the stationarity of time series data; the most popular is the Dickey-Fuller test. The Dickey-Fuller test formula generally examines the presence of a unit root in a time series. This test can be performed in various forms, but one of the most common forms, the basic Dickey-Fuller test model, is as follows:

$$Y_t = \alpha + \beta t + \rho Y_{t-1} + \epsilon t \quad (4)$$

Y_t is the value of the time series at time t, α is the intercept, β is the trend coefficient, ϱ is the unit root parameter, Y_{t-1} is the previous value of the time series, and ε_t is the random error.

Test hypotheses: null hypothesis $(\rho = 1)$ H_0 the time series has a unit root and is non-stationary. Alternative hypothesis: $(\rho < 1)$ H_1 the time series is stationary and does not have a unit root. The Dickey-Fuller test statistic is calculated as follows:

$$FDA = \frac{1-\rho^{\wedge}}{(\rho^{\wedge})ES}, \quad (5)$$

where: $\rho^{\wedge}$ is the estimated unit root parameter (using regression), and $(\rho^{\wedge})ES$ is the standard error of the estimate $\rho^{\wedge}$. In the augmented version, to control for autocorrelation, several lags are added to the model:

$$Y_t = \alpha + \sum_{i=1}^{p} \phi_i Y_{i-1} + \rho Y_{t-1} + \epsilon t \quad (6)$$

where p is the number of lags and ϕ_i are the coefficients corresponding to the lags?

By calculating the test statistic and comparing it with the critical values, the null hypothesis can be rejected or accepted. If the test statistic is less than the critical value (more negative), the null hypothesis is rejected, and we conclude that the time series is stationary. *Table 2* shows the results of the Dickey-Fuller test. The results of the Dickey-Fuller test indicate that all production data columns (except Saipa Diesel, which is marginally significant at the 1% level) are stationary. It means that time-series models like Box-Jenkins can be used for forecasting.

After examining the stationarity of the time series, the lag can be determined. The lag in a time series is the time interval between observations over which meaningful relationships for predicting future values exist. There are various methods for identifying lag in a time series. In this study, the Dickey-Fuller test and plotting autocorrelation and partial autocorrelation charts have been used. *Fig. 5* shows the autocorrelation and partial autocorrelation values for the Saipa company.

Table 2. Dickey-Fuller test results for examining dataset stationarity.

Company	Dickey-Fuller Test Statistic	P-Value	Critical Region	Time Lag
Saipa	-5.5858	1.36E-06	{'1%': -3.4413, '5%': -2.86637, '10%': -2.56934}	3
Pars Khodro	-4.3346	0.000386	{'1%': -3.4412, '5%': -2.86636, '10%': -2.569337}	3
Saipa Citroën	-5.6880	8.19E-07	{'1%': -3.44133, '5%': -2.86638, '10%': -2.56935}	8
Bonro	-4.3631	0.000344	{'1%': -3.44127, '5%': -2.86636, '10%': -2.569337}	13
Zamyad	-4.8148	5.09E-05	{'1%': -3.44127, '5%': -2.86636, '10%': -2.56933}	5
Saipa Diesel	-3.9388	0.001766	{'1%': -3.4413, '5%': -2.86637, '10%': -2.56934}	10

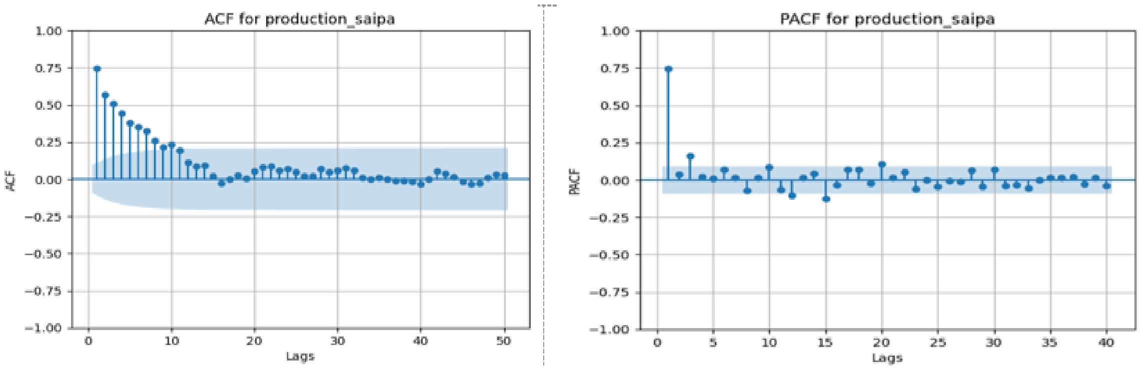

Fig. 5. Autocorrelation charts (with 10 significant time lags) and partial autocorrelation charts (with 15 significant time lags) for the Saipa Automotive Company.

3.2 | Model Implementation and Parameter Estimation

For the implementation, training, parameter estimation, and performance evaluation of the predictive models, the data is split into two sets: training (75%) and test (25%). Then, by implementing and running the auto-ARIMA model, the initial parameter values for the time series models are determined. Using this model, the upper bound of the ARIMA model coefficients is determined, so that only the performance of models with smaller coefficients is examined.

The approach to model validation and evaluation, along with a detailed explanation of the process for selecting the best predictive model, is provided. *Tables 3-5* sequentially present the training and implementation results of the model, using the Box-Jenkins method, for predicting the daily production of six automotive group companies: single-target models without exogenous variables and single-target models with exogenous variables (weekly plan).

Table 3. Selected single-target time series models without exogenous variables for predicting the SAIPA automotive group production.

Company | **Coefficient Table** | **Forecast Chart for Test Data** | **Evaluation Criteria Values**

Saipa

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                  428
Model:               SARIMAX(4, 1, 5)   Log Likelihood               -2910.614
Date:                Mon, 06 Jan 2025   AIC                           5841.228
Time:                        17:49:02   BIC                           5881.796
Sample:                    04-03-2023   HQIC                          5857.251
                         - 06-03-2024
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ar.L1         -1.2758      0.104    -12.279      0.000      -1.479      -1.072
ar.L2         -1.1646      0.165     -7.051      0.000      -1.488      -0.841
ar.L3         -0.8660      0.165     -5.236      0.000      -1.190      -0.542
ar.L4         -0.6182      0.100     -6.195      0.000      -0.814      -0.423
ma.L1          0.3599      0.076      4.754      0.000       0.212       0.508
ma.L2          0.1352      0.080      1.698      0.090      -0.021       0.291
ma.L3         -0.2870      0.072     -3.986      0.000      -0.428      -0.146
ma.L4         -0.2684      0.076     -3.547      0.000      -0.417      -0.120
ma.L5         -0.8337      0.070    -11.921      0.000      -0.971      -0.697
sigma2      5.538e+04   4893.037     11.318      0.000    4.58e+04     6.5e+04
===================================================================================
Ljung-Box (L1) (Q):                   3.40   Jarque-Bera (JB):                40.87
Prob(Q):                              0.07   Prob(JB):                         0.00
Heteroskedasticity (H):               1.16   Skew:                            -0.72
Prob(H) (two-sided):                  0.38   Kurtosis:                         2.54
===================================================================================
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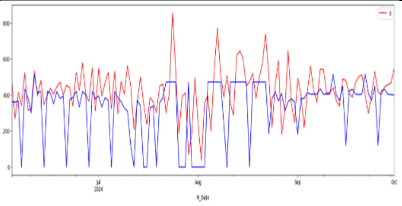

MSE=84228.015

RMSE=290.220

MAE=257.60

Pars khodro

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                  428
Model:               SARIMAX(4, 1, 3)   Log Likelihood               -2755.300
Date:                Mon, 06 Jan 2025   AIC                           5528.599
Time:                        16:03:19   BIC                           5565.110
Sample:                    04-03-2023   HQIC                          5543.020
                         - 06-03-2024
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
intercept     -0.1923      2.867     -0.067      0.947      -5.812       5.428
ar.L1         -1.4245      0.064    -22.088      0.000      -1.551      -1.298
ar.L2         -0.4634      0.119     -3.881      0.000      -0.697      -0.229
ar.L3          0.1220      0.117      1.045      0.296      -0.107       0.351
ar.L4         -0.1385      0.061     -2.253      0.024      -0.259      -0.018
ma.L1          0.8187      0.036     22.608      0.000       0.748       0.890
ma.L2         -0.6931      0.049    -14.066      0.000      -0.790      -0.597
ma.L3         -0.8774      0.035    -25.370      0.000      -0.945      -0.810
sigma2      2.971e+04   2969.736     10.004      0.000    2.39e+04    3.55e+04
===================================================================================
Ljung-Box (L1) (Q):                   0.00   Jarque-Bera (JB):                17.46
Prob(Q):                              0.96   Prob(JB):                         0.00
Heteroskedasticity (H):               0.60   Skew:                            -0.49
Prob(H) (two-sided):                  0.00   Kurtosis:                         2.86
===================================================================================
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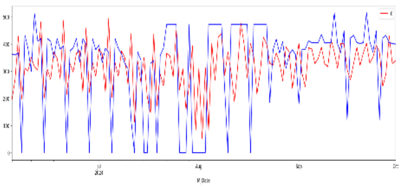


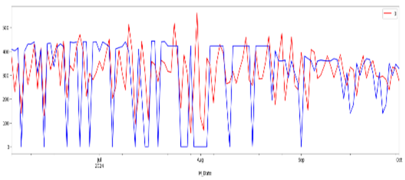
MSE=45189.1578

RMSE=672.231

MAE=449.285

Saipa citroën

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                  428
Model:               SARIMAX(4, 1, 4)   Log Likelihood               -2784.264
Date:                Mon, 06 Jan 2025   AIC                           5588.527
Time:                        18:34:18   BIC                           5629.095
Sample:                    04-03-2023   HQIC                          5604.551
                         - 06-03-2024
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
intercept     -0.5212      4.936     -0.106      0.916     -10.196       9.153
ar.L1         -0.9648      0.199     -4.847      0.000      -1.355      -0.575
ar.L2          0.1322      0.329      0.402      0.688      -0.513       0.777
ar.L3          0.1634      0.184      0.890      0.374      -0.197       0.524
ar.L4         -0.3728      0.079     -4.710      0.000      -0.528      -0.218
ma.L1          0.3162      0.193      1.635      0.102      -0.063       0.695
ma.L2         -1.0665      0.178     -6.005      0.000      -1.415      -0.718
ma.L3         -0.4167      0.125     -3.333      0.001      -0.662      -0.172
ma.L4          0.5540      0.172      3.230      0.001       0.218       0.890
sigma2      3.451e+04   3518.430      9.807      0.000    2.76e+04    4.14e+04
===================================================================================
Ljung-Box (L1) (Q):                   0.03   Jarque-Bera (JB):                27.87
Prob(Q):                              0.87   Prob(JB):                         0.00
Heteroskedasticity (H):               1.07   Skew:                            -0.62
Prob(H) (two-sided):                  0.70   Kurtosis:                         3.08
===================================================================================
```



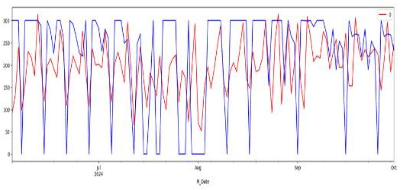
MSE= 24852.285

RMSE=157.649

MAE=116.2545

Bonro

```
                               SARIMAX Results
==============================================================================
Dep. Variable:                      y   No. Observations:                  428
Model:               SARIMAX(1, 0, 0)   Log Likelihood               -2572.114
Date:                Mon, 06 Jan 2025   AIC                           5150.227
Time:                        20:51:43   BIC                           5162.405
Sample:                    04-03-2023   HQIC                          5155.037
                         - 06-03-2024
Covariance Type:                  opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
intercept    141.5831      8.677     16.317      0.000     124.576     158.590
ar.L1          0.1964      0.050      3.889      0.000       0.097       0.295
sigma2      9720.0660   1441.326      6.744      0.000    6895.118    1.25e+04
===================================================================================
Ljung-Box (L1) (Q):                   0.04   Jarque-Bera (JB):                65.2
Prob(Q):                              0.83   Prob(JB):                         0.0
Heteroskedasticity (H):               1.87   Skew:                            -0.9
Prob(H) (two-sided):                  0.00   Kurtosis:                         2.4
===================================================================================
```



MSE=15018.9059

RMSE=122.5576

MAE=115.9825

Table 3. Continued.

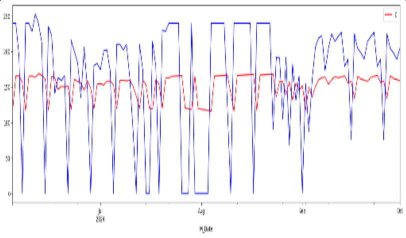
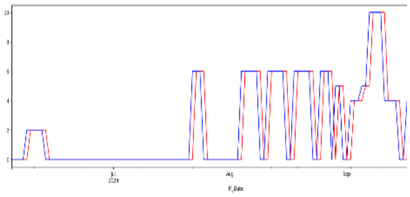
Company	Coefficient Table	Forecast Chart for Test Data	Evaluation Criteria Values
Zamyad	SARIMAX Results Dep. Variable: y · No. Observations: 428 Model: SARIMAX(1, 0, 0) · Log Likelihood -2493.213 Date: Mon, 06 Jan 2025 · AIC 4992.425 Time: 21:19:18 · BIC 5004.602 Sample: 04-03-2023 - 06-03-2024 · HQIC 4997.234 Covariance Type: opg coef · std err · z · P>|z| · [0.025 · 0.975] intercept 116.0103 · 6.765 · 17.148 · 0.000 · 102.751 · 129.270 ar.L1 0.2069 · 0.050 · 4.103 · 0.000 · 0.108 · 0.306 sigma2 6717.8233 · 836.711 · 8.029 · 0.000 · 5077.899 · 8357.747 Ljung-Box (L1) (Q): 0.01 · Jarque-Bera (JB): 48.44 Prob(Q): 0.91 · Prob(JB): 0.0 Heteroskedasticity (H): 1.70 · Skew: -0.7 Prob(H) (two-sided): 0.00 · Kurtosis: 2.3		MSE=7969.475 RMSE=89.2719 MAE=79.6305
Saipa diesel	SARIMAX Results Dep. Variable: y · No. Observations: 428 Model: SARIMAX(0, 1, 0) · Log Likelihood -1331.341 Date: Mon, 06 Jan 2025 · AIC 2664.682 Time: 21:22:01 · BIC 2668.739 Sample: 04-03-2023 - 06-03-2024 · HQIC 2666.285 Covariance Type: opg coef · std err · z · P>|z| · [0.025 · 0.975] sigma2 29.9016 · 0.855 · 34.966 · 0.000 · 28.226 · 31.578 Ljung-Box (L1) (Q): 0.03 · Jarque-Bera (JB): 1589.95 Prob(Q): 0.86 · Prob(JB): 0.00 Heteroskedasticity (H): 0.15 · Skew: 0.01 Prob(H) (two-sided): 0.00 · Kurtosis: 12.45		MSE=13.9650 RMSE=3.7369 MAE=2.4685

Table 4. Selected single-target time series models with exogenous variables (ARIMAX) for predicting the SAIPA automotive group production.

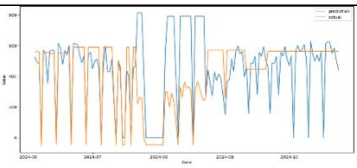
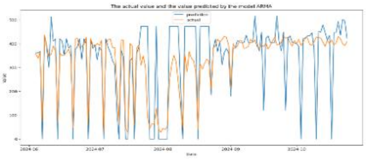
<table>
<tr><th>Company</th><th>Coefficient Table</th><th>Forecast Chart for Test Data</th><th>Evaluation Criteria Values</th></tr>
<tr><td>Saipa</td><td>
SARIMAX Results
<table>
<tr><td>Dep. Variable:</td><td>production_saipa</td><td>No. Observations:</td><td>428</td></tr>
<tr><td>Model:</td><td>ARIMA(4, 1, 5)</td><td>Log Likelihood</td><td>-2343.769</td></tr>
<tr><td>Date:</td><td>Mon, 06 Jan 2025</td><td>AIC</td><td>4709.538</td></tr>
<tr><td>Time:</td><td>18:17:23</td><td>BIC</td><td>4754.162</td></tr>
<tr><td>Sample:</td><td>04-03-2023
- 06-03-2024</td><td>HQIC</td><td>4727.164</td></tr>
<tr><td>Covariance Type:</td><td>opg</td><td></td><td></td></tr>
</table>
<table>
<tr><th></th><th>coef</th><th>std err</th><th>z</th><th>P>|z|</th><th>[0.025</th><th>0.975]</th></tr>
<tr><td>Week_Plan_saipa</td><td>0.7840</td><td>0.012</td><td>67.725</td><td>0.000</td><td>0.761</td><td>0.807</td></tr>
<tr><td>ar.L1</td><td>-0.1024</td><td>0.728</td><td>-0.141</td><td>0.888</td><td>-1.530</td><td>1.325</td></tr>
<tr><td>ar.L2</td><td>-0.4121</td><td>0.308</td><td>-1.336</td><td>0.181</td><td>-1.016</td><td>0.192</td></tr>
<tr><td>ar.L3</td><td>-0.2946</td><td>0.538</td><td>-0.547</td><td>0.584</td><td>-1.350</td><td>0.761</td></tr>
<tr><td>ar.L4</td><td>0.2661</td><td>0.212</td><td>1.256</td><td>0.209</td><td>-0.149</td><td>0.681</td></tr>
<tr><td>ma.L1</td><td>-0.5203</td><td>0.727</td><td>-0.716</td><td>0.474</td><td>-1.945</td><td>0.904</td></tr>
<tr><td>ma.L2</td><td>0.1810</td><td>0.458</td><td>0.395</td><td>0.693</td><td>-0.716</td><td>1.078</td></tr>
<tr><td>ma.L3</td><td>-0.0543</td><td>0.433</td><td>-0.125</td><td>0.900</td><td>-0.903</td><td>0.794</td></tr>
<tr><td>ma.L4</td><td>-0.6061</td><td>0.366</td><td>-1.655</td><td>0.098</td><td>-1.324</td><td>0.112</td></tr>
<tr><td>ma.L5</td><td>0.1714</td><td>0.264</td><td>0.648</td><td>0.517</td><td>-0.347</td><td>0.689</td></tr>
<tr><td>sigma2</td><td>3471.3854</td><td>196.531</td><td>17.663</td><td>0.000</td><td>3086.192</td><td>3856.578</td></tr>
</table>
<table>
<tr><td>Ljung-Box (L1) (Q):</td><td>0.00</td><td>Jarque-Bera (JB):</td><td>66.18</td></tr>
<tr><td>Prob(Q):</td><td>0.96</td><td>Prob(JB):</td><td>0.00</td></tr>
<tr><td>Heteroskedasticity (H):</td><td>1.15</td><td>Skew:</td><td>-0.37</td></tr>
<tr><td>Prob(H) (two-sided):</td><td>0.41</td><td>Kurtosis:</td><td>4.78</td></tr>
</table>
</td><td></td><td>MSE=50939.139
RMSE=225.667
MAE=147.098</td></tr>
<tr><td>Pars khodro</td><td>
SARIMAX Results
<table>
<tr><td>Dep. Variable:</td><td>production_Pars_Khodro</td><td>No. Observations:</td><td>428</td></tr>
<tr><td>Model:</td><td>ARIMA(3, 1, 3)</td><td>Log Likelihood</td><td>-2396.064</td></tr>
<tr><td>Date:</td><td>Mon, 06 Jan 2025</td><td>AIC</td><td>4808.129</td></tr>
<tr><td>Time:</td><td>17:35:19</td><td>BIC</td><td>4840.583</td></tr>
<tr><td>Sample:</td><td>04-03-2023
- 06-03-2024</td><td>HQIC</td><td>4820.948</td></tr>
<tr><td>Covariance Type:</td><td>opg</td><td></td><td></td></tr>
</table>
<table>
<tr><th></th><th>coef</th><th>std err</th><th>z</th><th>P>|z|</th><th>[0.025</th><th>0.975]</th></tr>
<tr><td>Week_Plan_Pars_Khodro</td><td>0.7473</td><td>0.014</td><td>52.789</td><td>0.000</td><td>0.720</td><td>0.775</td></tr>
<tr><td>ar.L1</td><td>0.0691</td><td>0.235</td><td>0.294</td><td>0.769</td><td>-0.391</td><td>0.529</td></tr>
<tr><td>ar.L2</td><td>0.8707</td><td>0.127</td><td>6.830</td><td>0.000</td><td>0.621</td><td>1.121</td></tr>
<tr><td>ar.L3</td><td>-0.1882</td><td>0.114</td><td>-1.645</td><td>0.100</td><td>-0.412</td><td>0.036</td></tr>
<tr><td>ma.L1</td><td>-0.6544</td><td>0.231</td><td>-2.827</td><td>0.005</td><td>-1.108</td><td>-0.201</td></tr>
<tr><td>ma.L2</td><td>-0.9599</td><td>0.032</td><td>-29.675</td><td>0.000</td><td>-1.023</td><td>-0.897</td></tr>
<tr><td>ma.L3</td><td>0.6330</td><td>0.214</td><td>2.960</td><td>0.003</td><td>0.214</td><td>1.052</td></tr>
<tr><td>sigma2</td><td>4357.9904</td><td>184.893</td><td>23.570</td><td>0.000</td><td>3995.607</td><td>4720.374</td></tr>
</table>
<table>
<tr><td>Ljung-Box (L1) (Q):</td><td>0.07</td><td>Jarque-Bera (JB):</td><td>638.33</td></tr>
<tr><td>Prob(Q):</td><td>0.79</td><td>Prob(JB):</td><td>0.00</td></tr>
<tr><td>Heteroskedasticity (H):</td><td>0.24</td><td>Skew:</td><td>-1.05</td></tr>
<tr><td>Prob(H) (two-sided):</td><td>0.00</td><td>Kurtosis:</td><td>8.61</td></tr>
</table>
</td><td></td><td>MSE=31094.542
RMSE=176.336
MAE=150.572</td></tr>
</table>

Table 4. Continued.

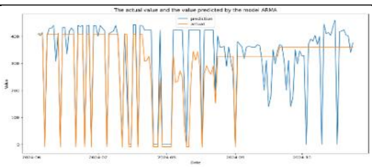
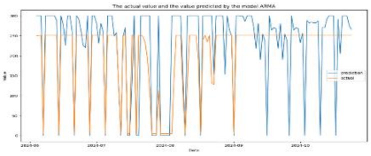
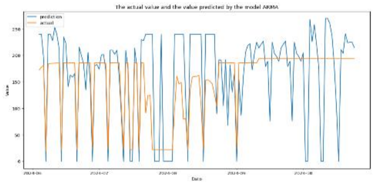
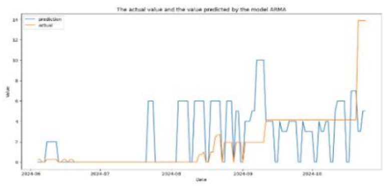
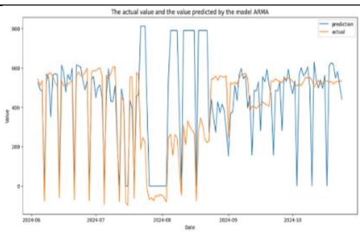
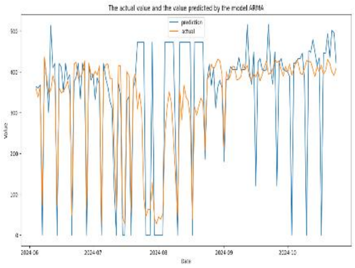
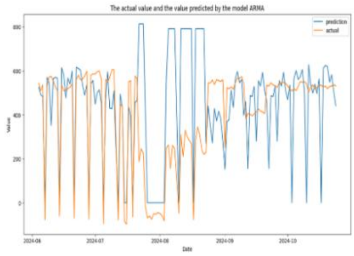
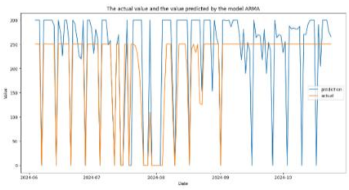
Company	Coefficient Table	Forecast Chart for Test Data	Evaluation Criteria Values
Saipa citroën	SARIMAX Results Dep. Variable: production_Citroen No. Observations: 428 Model: ARIMA(2, 1, 2) Log Likelihood -2301.074 Date: Mon, 06 Jan 2025 AIC 4614.148 Time: 20:39:24 BIC 4638.488 Sample: 04-03-2023 HQIC 4623.762 - 06-03-2024 Covariance Type: opg coef std err z P>|z| [0.025 0.975] Week_Plan_Citroen 0.7929 0.011 72.602 0.000 0.771 0.814 ar.L1 0.6489 0.407 1.596 0.111 -0.148 1.446 ar.L2 -0.0028 0.165 -0.017 0.987 -0.327 0.321 ma.L1 -1.2051 0.409 -2.947 0.003 -2.006 -0.404 ma.L2 0.2535 0.370 0.686 0.493 -0.471 0.978 sigma2 2800.6763 112.659 24.860 0.000 2579.869 3021.484 Ljung-Box (L1) (Q): 0.00 Jarque-Bera (JB): 350.92 Prob(Q): 1.00 Prob(JB): 0.00 Heteroskedasticity (H): 0.74 Skew: -0.70 Prob(H) (two-sided): 0.07 Kurtosis: 7.22		MSE= 547.079 RMSE=97.709 MAE=61.217
Bonro	SARIMAX Results Dep. Variable: production_Bonro No. Observations: 428 Model: ARIMA(1, 0, 0) Log Likelihood -2106.323 Date: Mon, 06 Jan 2025 AIC 4220.646 Time: 21:09:49 BIC 4236.882 Sample: 04-03-2023 HQIC 4227.058 - 06-03-2024 Covariance Type: opg coef std err z P>|z| [0.025 0.975] const 5.0332 6.791 0.741 0.459 -8.276 18.343 Week_Plan_Bonro 0.8207 0.023 35.068 0.000 0.775 0.867 ar.L1 0.3292 0.023 14.232 0.000 0.284 0.375 sigma2 1101.5779 42.108 26.160 0.000 1019.047 1184.109 Ljung-Box (L1) (Q): 0.20 Jarque-Bera (JB): 2360.51 Prob(Q): 0.65 Prob(JB): 0.00 Heteroskedasticity (H): 0.29 Skew: -2.32 Prob(H) (two-sided): 0.00 Kurtosis: 13.53		MSE=5848.7371 RMSE=76.4770 MAE=49.706
Zamyad	SARIMAX Results Dep. Variable: production_Zamiad No. Observations: 428 Model: ARIMA(1, 0, 0) Log Likelihood -2218.419 Date: Mon, 06 Jan 2025 AIC 4444.839 Time: 21:51:55 BIC 4461.075 Sample: 04-03-2023 HQIC 4451.251 - 06-03-2024 Covariance Type: opg coef std err z P>|z| [0.025 0.975] const 22.0228 6.765 3.255 0.001 8.763 35.283 Week_Plan_Zamiad 0.6826 0.017 39.552 0.000 0.649 0.716 ar.L1 0.6055 0.031 19.630 0.000 0.545 0.666 sigma2 1858.4529 81.867 22.701 0.000 1697.996 2018.909 Ljung-Box (L1) (Q): 6.41 Jarque-Bera (JB): 173.53 Prob(Q): 0.01 Prob(JB): 0.00 Heteroskedasticity (H): 3.55 Skew: -0.12 Prob(H) (two-sided): 0.00 Kurtosis: 6.11		MSE= 4749.805 RMSE=68.9188 MAE=48.5793
Saipa diesel	SARIMAX Results Dep. Variable: production_Diesel No. Observations: 428 Model: ARIMA(0, 1, 0) Log Likelihood -1306.642 Date: Mon, 06 Jan 2025 AIC 2617.285 Time: 21:55:28 BIC 2625.398 Sample: 04-03-2023 HQIC 2620.489 - 06-03-2024 Covariance Type: opg coef std err z P>|z| [0.025 0.975] Week_Plan_Diesel 0.2434 0.031 7.919 0.000 0.183 0.304 sigma2 26.6350 0.773 34.458 0.000 25.120 28.150 Ljung-Box (L1) (Q): 0.25 Jarque-Bera (JB): 1832.68 Prob(Q): 0.62 Prob(JB): 0.00 Heteroskedasticity (H): 0.12 Skew: -0.44 Prob(H) (two-sided): 0.00 Kurtosis: 13.11		MSE=10.6592 RMSE=3.2648 MAE=1.9755

Table 5. Selected single-target time series models with exogenous variables (SARIMAX) for predicting the SAIPA automotive group production.

Company	Coefficient Table	Forecast Chart for Test Data	Evaluation Criteria Values
Saipa			MSE=53531.336 RMSE=231.368 MAE=152.981
Pars khodro			MSE=11833.48 RMSE=108.782 MAE=69.5627
Saipa citroën			MSE=5351.3364 RMSE=231.368 MAE=152.9816
Bonro			MSE=5921.850 RMSE=76.953 MAE=49.4894

Saipa

```
                                    SARIMAX Results
==========================================================================================
Dep. Variable:                production_saipa   No. Observations:                  428
Model:             SARIMAX(4, 1, 5)x(4, 1, 5, 15)   Log Likelihood               -2313.977
Date:                     Mon, 06 Jan 2025   AIC                           4667.954
Time:                             18:26:32   BIC                           4748.375
Sample:                         04-03-2023   HQIC                          4699.764
                              - 06-03-2024
Covariance Type:                       opg
=====================================================================================
                        coef    std err          z      P>|z|      [0.025      0.975]
-------------------------------------------------------------------------------------
Week_Plan_saipa       0.7862      0.019     40.706      0.000       0.748       0.824
ar.L1                -1.1352      0.678     -1.674      0.094      -2.465       0.194
ar.L2                -0.0035      0.520     -0.007      0.995      -1.022       1.015
ar.L3                 1.1502      0.637      1.806      0.071      -0.098       2.399
ar.L4                 0.9373      0.419      2.239      0.025       0.117       1.758
ma.L1                 0.2874      5.934      0.048      0.961     -11.343      11.918
ma.L2                -1.0127      7.359     -0.138      0.891     -15.436      13.411
ma.L3                -1.1727      2.345     -0.500      0.617      -5.768       3.423
ma.L4                 0.0479      5.160      0.009      0.993     -10.066      10.162
ma.L5                 0.8501      4.777      0.178      0.859      -8.512      10.212
ar.S.L15             -1.6977      1.021     -1.663      0.096      -3.698       0.303
ar.S.L30             -1.6727      1.793     -0.933      0.351      -5.187       1.842
ar.S.L45             -1.7069      1.153     -1.480      0.139      -3.967       0.553
ar.S.L60             -0.8115      0.507     -1.601      0.109      -1.805       0.182
ma.S.L15              0.7666      2.608      0.294      0.769      -4.344       5.877
ma.S.L30              0.0418      3.322      0.013      0.990      -6.468       6.552
ma.S.L45              0.1628      3.241      0.050      0.960      -6.189       6.515
ma.S.L60             -0.8436      3.011     -0.280      0.779      -6.746       5.059
ma.S.L75             -0.7360      3.040     -0.242      0.809      -6.694       5.222
sigma2             5094.2497    2.8e+04      0.182      0.856   -4.98e+04       6e+04
=====================================================================================
Ljung-Box (L1) (Q):                  21.55   Jarque-Bera (JB):                64.55
Prob(Q):                              0.00   Prob(JB):                         0.00
Heteroskedasticity (H):               1.06   Skew:                            -0.44
Prob(H) (two-sided):                  0.73   Kurtosis:                         4.73
=====================================================================================
```

Pars khodro

```
                                    SARIMAX Results
==========================================================================================
Dep. Variable:           production_Pars_Khodro   No. Observations:                  428
Model:             SARIMAX(3, 1, 3)x(3, 1, 3, 15)   Log Likelihood               -2341.176
Date:                     Mon, 06 Jan 2025   AIC                           4710.351
Time:                             17:40:33   BIC                           4766.646
Sample:                         04-03-2023   HQIC                          4732.619
                              - 06-03-2024
Covariance Type:                       opg
==========================================================================================
                            coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------------------
Week_Plan_Pars_Khodro     0.7466      0.015     51.482      0.000       0.718       0.775
ar.L1                    -1.5586      0.053    -29.137      0.000      -1.663      -1.454
ar.L2                    -0.3098      0.095     -3.261      0.001      -0.496      -0.124
ar.L3                     0.3572      0.049      7.291      0.000       0.261       0.453
ma.L1                     1.0019      0.050     19.990      0.000       0.904       1.100
ma.L2                    -0.7475      0.047    -15.966      0.000      -0.839      -0.656
ma.L3                    -0.9049      0.047    -19.351      0.000      -0.997      -0.813
ar.S.L15                 -0.2240      4.784     -0.047      0.963      -9.601       9.153
ar.S.L30                  0.8307      3.536      0.235      0.814      -6.099       7.760
ar.S.L45                  0.0630      0.287      0.220      0.826      -0.499       0.625
ma.S.L15                 -0.8724      4.635     -0.188      0.851      -9.956       8.211
ma.S.L30                 -0.9869      8.116     -0.122      0.903     -16.894      14.920
ma.S.L45                  0.8691      3.826      0.227      0.820      -6.630       8.369
sigma2                 4463.1933   1920.130      2.324      0.020     699.808    8226.579
=====================================================================================
Ljung-Box (L1) (Q):                   0.22   Jarque-Bera (JB):               293.60
Prob(Q):                              0.64   Prob(JB):                         0.00
Heteroskedasticity (H):               0.26   Skew:                            -0.91
Prob(H) (two-sided):                  0.00   Kurtosis:                         6.71
=====================================================================================
```

Saipa citroën

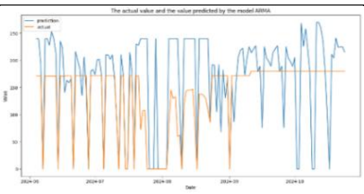
```
                                    SARIMAX Results
==========================================================================================
Dep. Variable:              production_Citroen   No. Observations:                  428
Model:             SARIMAX(2, 1, 2)x(2, 1, 2, 15)   Log Likelihood               -2248.004
Date:                     Mon, 06 Jan 2025   AIC                           4516.009
Time:                             20:46:28   BIC                           4556.219
Sample:                         04-03-2023   HQIC                          4531.914
                              - 06-03-2024
Covariance Type:                       opg
======================================================================================
                         coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------------
Week_Plan_Citroen      0.7955      0.011     70.509      0.000       0.773       0.818
ar.L1                  0.9108      0.221      4.129      0.000       0.479       1.343
ar.L2                 -0.0968      0.123     -0.787      0.431      -0.338       0.144
ma.L1                 -1.4800      0.215     -6.893      0.000      -1.901      -1.059
ma.L2                  0.4925      0.206      2.393      0.017       0.089       0.896
ar.S.L15               0.5038      3.198      0.158      0.875      -5.764       6.772
ar.S.L30              -0.0101      0.198     -0.051      0.959      -0.398       0.377
ma.S.L15              -1.3987      3.230     -0.433      0.665      -7.730       4.933
ma.S.L30               0.4241      3.045      0.139      0.889      -5.544       6.392
sigma2              2931.8657    224.755     13.045      0.000    2491.355    3372.377
===================================================================================
Ljung-Box (L1) (Q):                   0.08   Jarque-Bera (JB):               185.41
Prob(Q):                              0.78   Prob(JB):                         0.00
Heteroskedasticity (H):               0.75   Skew:                            -0.56
Prob(H) (two-sided):                  0.09   Kurtosis:                         6.09
===================================================================================
```

Bonro

```
                                    SARIMAX Results
==========================================================================================
Dep. Variable:                production_Bonro   No. Observations:                  428
Model:             SARIMAX(1, 0, 0)x(1, 0, 0, 15)   Log Likelihood               -2107.197
Date:                     Mon, 06 Jan 2025   AIC                           4222.394
Time:                             21:15:44   BIC                           4238.631
Sample:                         04-03-2023   HQIC                          4228.807
                              - 06-03-2024
Covariance Type:                       opg
===================================================================================
                      coef    std err          z      P>|z|      [0.025      0.975]
-----------------------------------------------------------------------------------
Week_Plan_Bonro     0.8352      0.011     75.812      0.000       0.814       0.857
ar.L1               0.3273      0.022     14.641      0.000       0.284       0.371
ar.S.L15            0.0076      0.050      0.154      0.878      -0.090       0.105
sigma2           1106.0652     42.378     26.100      0.000    1023.006    1189.125
===================================================================================
Ljung-Box (L1) (Q):                   0.29   Jarque-Bera (JB):              2482.38
Prob(Q):                              0.59   Prob(JB):                         0.00
Heteroskedasticity (H):               0.28   Skew:                            -2.38
Prob(H) (two-sided):                  0.00   Kurtosis:                        13.79
===================================================================================
```

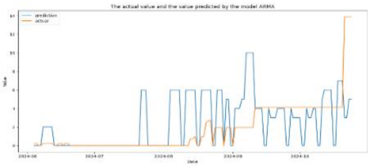
Table 5. Continued.

<table>
<tr><th>Company</th><th>Coefficient Table</th><th>Forecast Chart for Test Data</th><th>Evaluation Criteria Values</th></tr>
<tr><td>Zamyad</td><td>SARIMAX Results
==
Dep. Variable: production_Zamiad No. Observations: 428
Model: SARIMAX(1, 0, 0)x(1, 0, 0, 15) Log Likelihood -2223.834
Date: Mon, 06 Jan 2025 AIC 4455.668
Time: 21:58:46 BIC 4471.905
Sample: 04-03-2023 HQIC 4462.081
- 06-03-2024
Covariance Type: opg
==
coef std err z P>|z| [0.025 0.975]

Week_Plan_Zamiad 0.7142 0.014 50.372 0.000 0.686 0.742
ar.L1 0.6545 0.033 19.827 0.000 0.590 0.719
ar.S.L15 -0.0123 0.054 -0.228 0.820 -0.118 0.094
sigma2 1914.4419 85.515 22.387 0.000 1746.835 2082.049
==
Ljung-Box (L1) (Q): 12.31 Jarque-Bera (JB): 198.66
Prob(Q): 0.00 Prob(JB): 0.00
Heteroskedasticity (H): 3.63 Skew: -0.11
Prob(H) (two-sided): 0.00 Kurtosis: 6.33
==</td><td>
</td><td>MSE= 425.470

RMSE= 3.6577

MAE=51.297</td></tr>
<tr><td>Saipa Diesel</td><td>SARIMAX Results
==
Dep. Variable: production_Diesel No. Observations: 428
Model: SARIMAX(0, 1, 0)x(0, 1, 0, 15) Log Likelihood -1382.166
Date: Mon, 06 Jan 2025 AIC 2768.332
Time: 22:02:11 BIC 2776.374
Sample: 04-03-2023 HQIC 2771.513
- 06-03-2024
Covariance Type: opg
==
coef std err z P>|z| [0.025 0.975]

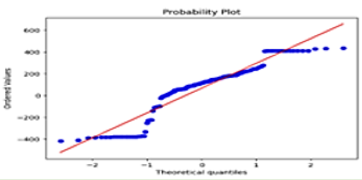
Week_Plan_Diesel 0.2014 0.024 8.370 0.000 0.154 0.249
sigma2 48.0229 1.831 26.233 0.000 44.435 51.611
==
Ljung-Box (L1) (Q): 0.79 Jarque-Bera (JB): 380.12
Prob(Q): 0.37 Prob(JB): 0.00
Heteroskedasticity (H): 0.14 Skew: 0.15
Prob(H) (two-sided): 0.00 Kurtosis: 7.70
==</td><td>
</td><td>MSE=150.50

RMSE=12.2678

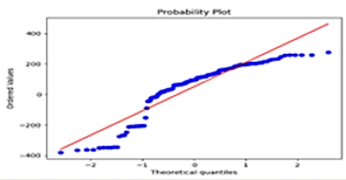
MAE=10.6670</td></tr>
</table>

3.3 | Model Validation and Evaluation

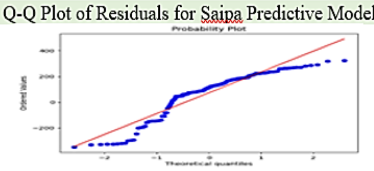
To validate the models and examine the normality of the residual distribution, a Q-Q plot (Fig. 6) has been used. A Q-Q plot shows the quantiles of a distribution. To check the normality of the data using a Q-Q plot, if the points lie approximately on a straight line, it indicates that the data are normally distributed. Deviation from the straight line may indicate that the data distribution is not normal. By examining the plots, the error distributions in all production data columns (except Saipa Diesel, which is weaker at the 1% level) appear normal. Regarding Saipa Diesel's production, due to frequent holidays and almost no production variance, the predictive model is equal to the company's constant average production, which has also affected the error distribution. According to industry experts, this model has accepted for predicting Saipa Diesel.



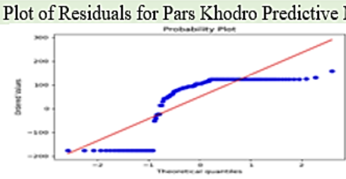
Q-Q Plot of Residuals for Saipa Predictive Model



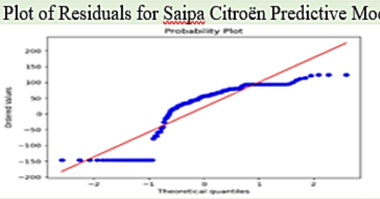
Q-Q Plot of Residuals for Pars Khodro Predictive Model



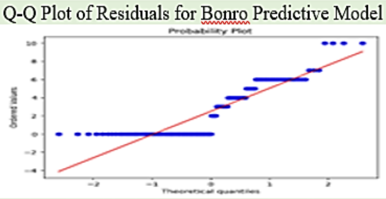
Q-Q Plot of Residuals for Saipa Citroën Predictive Model



Q-Q Plot of Residuals for Bonro Predictive Model



Q-Q Plot of Residuals for Zamyad Predictive Model



Q-Q Plot of Residuals for Saipa Diesel Predictive Model

Fig. 6. Q-Q Plots of residuals for predictive models in the SAIPA automotive group companies.

3.4 | Selecting the Best Performing Model

To fully explain the process of selecting the best predictive model, the process for selecting the best-performing model for the Saipa company is provided. Using the Box-Jenkins method and the auto-ARIMA model, time series models have been trained on the dataset. The auto-ARIMA model reports the best performing model based on BIC and AIC values. The best-performing model for predicting SAIPA's daily production, based on the auto-ARIMA results, is the ARIMA (4,1,5) model, with evaluation criteria values of AIC=5841.227, BIC=5881.795, MSE=84228.0155, RMSE=290.220, and MAE=257.60.

Then, the proposed model and models with smaller coefficients are implemented on the dataset, and the best performing model is selected based on AIC, BIC, MAE, MSE, and RMSE criteria, as well as its simplicity. As shown in *Fig. 7* and *Fig. 8*, models with smaller coefficients have been executed on the dataset, and the evaluation criteria values for these models have been obtained. Compared to the proposed auto-ARIMA model, the ARIMA (4,1,5) model still performs best at predicting the data. Additionally, the predictive model with the exogenous variable (weekly plan) for each company was executed. The best-performing model for predicting Saipa's daily production is the ARIMAX (4,1,5) model, with evaluation criteria values of AIC=4709.518, BIC=4754.164, MSE=50939.139, RMSE=225.667, and MAE=147.098. Following this, the SARIMAX (4,1,5) model, with evaluation criteria values of AIC=4667.954, BIC=4748.375, MSE=53531.336, RMSE=231.368, and MAE=152.981, performs worse. This process has also been used to select the best-performing model for other companies.

```
Auto_ARIMA (4,1,5) Model Information: AIC=5841.22766423708, BIC=5881.795504369366, LLF=-2910.61383211854
AR (1,0,0) Model Information: AIC=5987.714305927808, BIC=5995.827873954265, LLF=-2991.857152963904
AR (2,0,0) Model Information: AIC=5961.032564027664, BIC=5973.20291606735, LLF=-2977.516282013832
AR (3,0,0) Model Information: AIC=5947.820274608606, BIC=5964.047410661521, LLF=-2969.910137304303
MA (0,0,1) Model Information: AIC=5870.586387574196, BIC=5878.699955600653, LLF=-2933.293193787098
MA (0,0,2) Model Information: AIC=5870.10545643893, BIC=5882.2758084786155, LLF=-2932.052728219465
MA (0,0,3) Model Information: AIC=5868.648654231038, BIC=5884.8757902839525, LLF=-2930.324327115519
ARIMA (1,1,1) Model Information: AIC=5869.610984906441, BIC=5881.781336946127, LLF=-2931.8054924532207
ARIMA (2,1,2) Model Information: AIC=5869.610984906441, BIC=5881.781336946127, LLF=-2931.8054924532207
ARIMA (3,1,3) Model Information: AIC=5869.610984906441, BIC=5881.781336946127, LLF=-2931.8054924532207
```

Fig. 7. Evaluation criteria values for AIC, BIC, and LLF.

```
Auto_ARIMA (4,1,5) validation_metrics:
r2= -0.49279136078162167  mse= 84228.01551677268  rmse= 290.2206324794512  mae= 257.59889041424776
None
AR (1,0,0) validation_metrics:
r2= -1.3550599844134354  mse= 132879.94164585962  rmse= 364.5270108590852  mae= 331.9571083988821
None
AR (2,0,0) validation_metrics:
r2= -0.7628467483858967  mse= 99465.39561898005  rmse= 315.38134951036665  mae= 288.1231392875356
None
AR (3,0,0) validation_metrics:
r2= -0.7647001680484549  mse= 99569.97142521683  rmse= 315.5470985846912  mae= 288.1903746548931
None
MA (0,0,1) validation_metrics:
r2= -0.07304471590679507  mse= 60544.58068022681  rmse= 246.05808395626187  mae= 207.76272901143716
None
MA (0,0,2) validation_metrics:
r2= -0.07144903080376008  mse= 60454.54707395785  rmse= 245.87506395313423  mae= 207.37736224519284
None
MA (0,0,3) validation_metrics:
r2= -0.08506443583652423  mse= 61222.771339247236  rmse= 247.43235709835372  mae= 210.20843964241755
None
ARIMA (1,1,1) validation_metrics:
r2= -0.07371964280099053  mse= 60582.6621927613  rmse= 246.13545496892823  mae= 207.85412400005396
None
ARIMA (2,1,2) validation_metrics:
r2= -0.07237401324123427  mse= 60506.73751204797  rmse= 245.98117308454314  mae= 207.32911891502846
None
ARIMA (3,1,3) validation_metrics:
r2= -0.07478657685084289  mse= 60642.86199031325  rmse= 246.25771458030152  mae= 207.91718355002098
```

Fig. 8. Evaluation criteria values for MAE, MSE, RMSE, and R-squared.

3.5 | Result and Rolling Forecast

After implementation, validation, evaluation, and comparison of the results, the best time series forecasting models were selected as shown in Fig. 6. In this section, using a rolling or moving window approach, the daily production values for the SAIPA automotive group were forecast. To implement the rolling forecasting approach, the model parameters were updated every 30 days over the last three months of the dataset. *Fig. 9* shows the rolling forecasting method used in the research.

Table 6. Evaluation criteria values of the best forecasting model for the SAIPA automotive group companies.

	Saipa		Pars Khodro		Saipa Citroën	
	ARIMA	**ARIMAX**	**ARIMA**	**SARIMAX**	**ARIMA**	**ARIMAX**
MSE	84228.015	50939.139	45189.1578	11833.48	24852.285	5547.079
RMSE	290.220	225.667	672.231	108.782	157.649	97.709
MAE	257.60	147.098	449.285	69.5627	116.2545	61.217
	Bonro		**Zamyad**		**Saipa Diesel**	
	AR	**ARIMAX**	**AR**	**ARIMAX**	**---**	**ARIMAX**
MSE	15018.9059	5848.7371	7969.475	4749.805	13.9650	10.6592
RMSE	122.5576	76.4770	89.2719	68.9188	3.7369	3.2648
MAE	115.9825	49.706	79.6305	48.5793	2.4685	1.9755

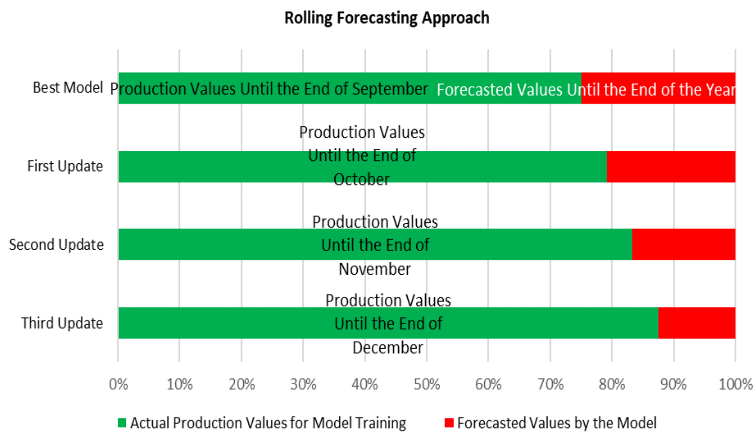


Fig. 9. Rolling forecasting approach and updating parameters of the best model in October, November, and December.

In *Table 7*, the mean absolute errors for the parameter update stages of the selected forecasting models are presented. It is expected that by updating the parameters based on new data, the forecasting models' error will decrease. However, this did not happen in the second update. This argument stems from an unexpected production decrease in October, highlighting the importance of patterns and data analysis for accurate forecasting. In *Fig. 10*, the forecasted production values for December for the update stages, the actual production statistics in this period, and the better performance of the third update are shown.

Table 7. MAE values based on parameter update stages of selected forecasting models for SAIPA.

Performance Evaluation Metric	First Update	Second Update	Third Update
MAE for October	253.1745	-------	-------
MAE for November	361.9097	366.9636	-------
MAE for December	227.9702	255.3307	209.3926

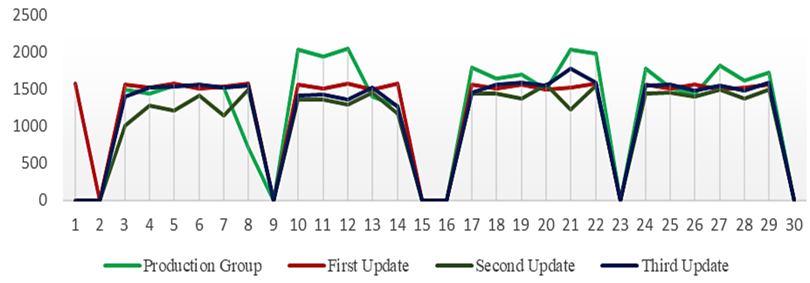


Fig. 10. Comparison of forecasted production values for update stages and actual production statistics in December.

4 | Conclusion

This study examined and forecasted production for the SAIPA automotive group using statistical time-series models. The results indicate that the ARIMAX model is the best for forecasting daily production. This model has provided more accurate forecasts by incorporating an exogenous variable (weekly production schedule). However, to achieve accurate forecasting models, examining and controlling production based solely on production trends, the ARIMA and AR models have performed better. The SARIMA and SARIMAX models, which are typically used for seasonal data, performed poorly in this study. This result may be due to the lack of strong seasonal patterns in daily production data. However, this result may change when examining cumulative forecasts of weekly or monthly values.

Using the rolling forecasting approach only in the first and second stages has reduced errors and improved forecast accuracy. It indicates that not only is the selection of an appropriate model and parameter optimization crucial for achieving more accurate forecasts, but also the examination and analysis of data patterns and unexpected trends are essential for achieving an optimal forecasting model.

Suggestions for future research include using more advanced models, such as artificial intelligence and machine learning, and employing more complex models, such as neural networks and deep learning, for production forecasting. Other practical applications of this research include developing software tools to assist managers in decision-making based on production forecasts. These tools can help improve production planning and inventory management. Given the results and suggestions, this research is expected to improve production processes in the automotive industry and other similar industries and to pave the way for further research in this field.

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Data Availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

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